APPLICATION OF SEASONAL MODELS IN MODELING AND FORECASTING THE MONTHLY PRICE OF PRIVILEGED SADRI RICE IN GUILAN PROVINCE

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ABSTRACT

The present research has considered modeling and forecasting the monthly price of Privileged Sadri rice in Guilan province using time series data for the years 2002-2011in Guilan province which is one of the rice production poles in Iran. In this context, using parametric and non-parametric models, monthly price of Privileged Sadri rice for 2012-4 to 2013-3 was forecasted. Non-parametric and parametric models used in this study are TES and SARMA, respectively. Results from comparing the amounts of MAPE within sample forecast error index between the two TES and SARMA models in this research showed that SARMA parametric model enjoys the most power in modeling the time series of monthly retail prices of Privileged Sadri rice and, thus it is the most appropriate model for forecasting the monthly retail price of Privileged Sadri rice.

Keywords: privileged sadri rice, modeling and price forecasting, non-parametric model, parametric model, guilan province.

INTRODUCTION

Among the economic sectors in a developing country agriculture sector as an important supplier of food is of considerable importance [1]. In order to increase the efficiency of economy of Iran, it is also necessary to pay special attention to agriculture sector as one of the main and important economic activities in the country, because at the present time it allocates about 15 percent of gross domestic products, 21 percent of occupation, and 22 percent of non-oil exports of the country to itself. Also, it has provided 80.1% of food supply units and 90% of needs of units of processing industries during the recent decade (statistics of agriculture). Agriculture sector is included in activities that are always at risk and thus, in most cases farmers are uncertain about their future income; risks in agriculture activities may be due to fluctuations in production price and / or government policies [2]. In case of agriculture products, presence of a risk is an accepted issue and the risk space has been led to decrease in paying attention to these activities as investment activities. Agriculture risk has the two production, and market or price risks. Predictions about the price of agriculture products can be an important step in the same line with market risk management. One of the agriculture products features is presence of distance between the time of decision making for production and the time of supplying to the market. This condition leads to little opportunity to deal with adverse market conditions. In such circumstances, policy makers with prior notice of the policy of production and product market and the required intervene can create some kind of supply management and prevent extreme price fluctuations [3].

Predicting the price of agricultural products helps farmers earn incomes as well as marketing factors, particularly, warehousing, and it is a key element in their decision makings. This is because the prices play the main role in optimizing the marketing production and market strategy [4]. In addition to the mentioned cases, price production has also an important role in government's policies. This is because government formulates and implements its policies not solely on the basis of the existing policies but based on short and long term predictions of key economic variables such as agricultural products.

Among the agricultural products, rice is of special importance and its use in the country has also been increased in line with improvement in family income and after the wheat, has taken the second place for itself in food pattern of the country. Considering that rice has the highest gross value among all agricultural products as well as higher income than other products, farmers take actions to cultivate this product.

In Iran, Guilan and Mazandaran provinces are among the major producers of rice, and they have large shares in production of this strategic product. The value of land in the provinces of Mazandaran and Guilan is very high, thus maintaining these lands and stability of production is very important. The Ministry of Agriculture does not allow usage changes in paddy fields, and its aim in 2013 is the policy of self-sufficiency in rice. Forecasting and modeling the prices of agricultural products bear remarkable importance in productive planning and policy, and this prevents severe swelling in market as well as farmers' disadvantages. It also causes the government to apply the policy of market regulation and also supportive policy such as guarantee buying and subside payment in case of this product for the purpose of planning for future of farmers. In most studies parametric and non-parametric methods have been used for modeling and predicting the prices [5, 3]. Using ARIMA and

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harmonic models, Saboor and Ershadolhagh [6] studied the fluctuations in time, seasonal and cyclic trends of wholesale prices of rice in Bangladesh and determined the future wholesale prices of rice. Using daily data for the years 1971-1990, Wow and Lu [7] predicted the stock price index in the United States of America. In this study ARIMA process and a three-layer feed forward neural network were used. In order to study the efficiency of the above methods, the mean absolute error criterion (MAD) was also applied. Noochia and Noochia [8] selected ARIMA model for prediction of price of palm oil in Thailand. They also predicted on farm and wholesale prices of net oil during the years 2000-2004, i.e., a 5 year period. The purpose of this study was to find an appropriate ARIMA model to predict the three different types of prices of palm oil considering the Minimum standard error of measurement (MAPE). Using the three models of ARIMA, BP and MSOA, Haofi et al., [9] predicted short term price of wheat in China. Results showed that after the publication algorithm (BP) was faced with some difficulties such as weak and gradual convergence, so a multi-stage optimization model (MSOA) was used to overcome the BP weaknesses. Prediction of MSOA model is more accurate than those of BP and ARIMA models. In their research, Suleman and Sarpong [14] used Box-Jenkins [13] method for predicting the rice-flour production in Ghana during ten future years. They used time series data for 1960-2010. Their analysis showed that ARIMA model is the best model for prediction of rice-flour production. Using time series data for the years 1970-2004, Farajzadeh and Shahvali [5] studied the nominal and real prices of agricultural products, including cotton, saffron and rice. After the study, form among the used models for prediction, including ARIMA, single and dual exponential smoothing, harmonic, ARCH and artificial neural network model on the basis of the criterion of minimum error prediction, ARIMA model predicted the series of nominal prices of rice and saffron better than other methods. And the best prediction for series of nominal and real prices of cotton was also obtained using artificial neural and harmonic network. In their studies, Fahimifard et al., [11] used regressional-neural network model with exogenous inputs for predicting retail prices of rice, chicken meat and egg, within three future time horizons and compared its efficiency with ARIMA model as the most common linear method for prediction. Results from evaluation of these models' efficiencies showed that in predicting retail prices of agricultural products within under consideration time horizons, non-linear model of regressional- neural network (NNARX) was more efficient than ARIMA linear model. In their studies for predicting the bankruptcy, Makian et al., [12] used artificial neural network and compared it with the two methods of logistic regression and discriminant analysis. In addition to introducing neural-artificial network, they also used a neural network for bankruptcy prediction of designed productive companies for Kerman province. Results from this research show that ANN model bears higher accuracy than other two

statistical methods in prediction. ANN model also showed that in the year after under consideration time period, none of these productive companies would experience bankruptcy.

Predicting the price of Sadri - e - Momtaz rice in future years has provided an appropriate framework for planners in order to regulate and apply market risk-management and through offering future income perspective for farmers; it brings a suitable means for the purpose of productive and optimized planning. Using parametric and non-parametric approaches, the present research has considered modeling and predicting per kilo price of Sadri - e - Momtaz rice for time series of the years 2002-2011.

MATERIALS AND METHODS

The used non-parametric model to predict the monthly retail price of Sadri - e - Momtaz rice Triple Exponential Smoothing model. On the other hand, Autoregressive Integrated Moving Average (ARIMA) expanded parametric approach will also be used in line with modeling and predicting. Then characteristics of each one of these models will briefly be examined.

Triple exponential smoothing (TES)

Dual Exponential Smoothing can be improved by adding seasonal effect modeling to consider the components obtained from analysis of time series data in a complete manner. Solution algorithm in TES can be demonstrated as follows:

$$F(t) = \alpha[x(t)/S(t-c)] + (1-\alpha)[F(t-1) + T(t-1)]$$
$$T(t) = \beta[F(t) - F(t-1)] + (1-\beta)T(t-1)$$
$$S(t) = \gamma[x(t)/F(t)] + (1-\gamma)S(t-c)$$
$$f(t+h) = [F(t) + hT(t)]S(t+h-c) \quad for \ h = 1, 2, ..., c$$
$$f(t+h) = [F(t) + hT(t)]S(t+h-2c) \quad for \ h = c+1, c+2, ..., 2c$$
$$f(t+h) = [F(t) + hT(t)]S(t+h-3c) \quad for \ h = 2c+1, 2c+2, ..., 3c$$
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$$c \ is \ the \ length \ of \ seasonal \ cycle$$
$$\alpha, \beta, \gamma \ are \ the \ smoothing \ con. \ 0 \le \alpha, \beta, \gamma \le 1$$
$$F(0) = \mu, \ the \ average \ of \ the \ first \ cycle \ t = 1 \ to \ c$$
$$T(0) = 0$$
$$S(t) = x(t)/\mu \ for \ t = 1 \ to \ c \qquad\qquad (1)$$

Seasonal autoregressive integrated moving average (SARIMA)

The general formula of SARIMA for monthly time series retail price of Sadri - e - Momtaz rice (WC) is as follows:

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$$\phi(L)\Phi(L^S)(1-L)^d(1-L^S)^D WC_t = \theta(L)\Theta(L^S)\varepsilon_t$$

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - ... - \phi_p L^p$$

$$\Phi(L^S) = 1 - \Phi_1 L^S - \Phi_2 L^{2S} - ... - \Phi_P L^{PS}$$

$$\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - ... - \theta_q L^q$$

$$\Theta(L^S) = 1 - \Theta_1 L^S - \Theta_2 L^{2S} - ... - \Theta_Q L^{QS} \qquad (2)$$

in the above mode, p, d, and q are autoregressive degree, differentiating, and non-seasonal moving average, respectively, and P, D, and Q are autoregressive degree, differentiating, and seasonal moving average, respectively. $_t$ is error sentence bearing the conditions of white noise (accidental shock) and S is seasonal degree for monthly data equal to 12. In order to estimate the model, at first time series stationary should be studied. Stationary means fixedness of average amounts, variance and autocorrelation of time series during the passage of time. If time series is stationary, average of each subset of time series should not be statistically and significantly different from other subset. On the other hand, variance of each subset of time series will, only accidently, be different from variance of other subset. Establishment of stationary, stability conditions are together with autoregressive regression coefficients of along a certain interval, and they will also guarantee the inevitability of autoregressive regression coefficients. Upon meeting the above conditions, the ground will be ready for prediction using the fitted model. In order to test the stationary of time series, existence or lack of the unit root is studied. Unit root test is to determine the presence or lack of Stochastic or deterministic trend in time series. If unit roots are outside the unit circle, time series will be stationary. In other words, if the fitted model coefficients according to absolute values are less than unit, time series are static. In order to perform stationary test for time series with seasonal and non-seasonal behavior, used test should include seasonal and non-seasonal components. In this regard, statistical tests such as HEGY, CH, BM, FH, and TAYLER can be used.

In HEGY approach in order to test unit root for monthly time series, an autoregressive model is created, so that roots of seasonal unit and long term unit are introduced by this model's regression coefficients. The mentioned autoregressive model is in general form A= $A(L)y_t = \varepsilon_t$, Where ε_t is the white noise and A (L) is continuous operator of grade twelve. Above said process is will be stationary when all roots of polynomial A (L) are outside the unit circle. In order to test the unit root of the mentioned model, expansion of polynomial A (L) = 1 - L^{12} will be used. Monthly time series analysis to determine unit roots is done using the following equation:

$$\Delta_{12} = (1-L)(1+L)(1+L^2)(1+L+L^2)(1-L+L^2)(1+\sqrt{3}L+L^2)(1-\sqrt{3}L+L^2) \quad (3)$$

On this basis, monthly seasonal and non-seasonal unit roots in the order from left to right are as follows:

$$\pm 1, \pm i, -\frac{1}{2}(\sqrt{3}\pm i), \frac{1}{2}(\sqrt{3}\pm i), -\frac{1}{2}(1\pm i\sqrt{3}), \frac{1}{2}(1\pm i\sqrt{3}) \qquad (4)$$

Above roots are respectively related to the cycles of ∞, 6, 3, 9, 8, 4, 2, 10, 7, 5, 1and 11 in each year and their frequencies are respectively as $0, \pi, \pm\pi/2$, $\mp 2\pi/3, \pm\pi/3, \mp 5\pi/6$, and $\pm\pi/6$.

In order to do monthly data unit roots tests the unit root test, formation of the test hypothesis should be done regardless of the presence or absence of other roots. In this regard, using Taylor approximation linear changes from under consideration monthly time series are created and this provides the test possibility for the presence of each unit root regardless of presence or absence of other roots. In this regard, general form of this test for monthly retail sales price of Sadri - e - Momtaz rice is as follows:

$$\Delta_{12}WC_t = \alpha + \beta T + \sum_{s=1}^{11}\delta_s D_{s,t} + \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-1} + \pi_4 y_{3,t-2}$$

$$\pi_5 y_{4,t-1} + \pi_6 y_{4,t-2} + \pi_7 y_{5,t-1} + \pi_8 y_{5,t-2} + \pi_9 y_{6,t-1} + \pi_{10} y_{6,t-2}$$

$$\pi_{11} y_{7,t-1} + \pi_{12} y_{7,t-2} + \sum_{i=1}^{p}\lambda_i \Delta_{12}WC_{t-i} + \varepsilon_t \qquad (5)$$

In the above relation, certain components include intercept (α), monthly imaginary variables (D) and process (T). Linear conversions will also be entered in the equation to test the presence of seasonal and non-seasonal roots. Used data in this research is related to monthly time series data from 2002 to 2011, and this has been obtained from Agricultural Jihad of Guilan province.

RESULTS AND DISCUSSIONS

Statistical properties of time series of monthly retail price of Sadri - e - Momtaz rice

In order for modeling time series of monthly retail price of Sadri -e - Momtaz , monthly data for 2002-2011 was considered. Studying the time trend of this series is indicative of growing trend and together with momentum during the mentioned period. The growing trend of data during the period studied is easily observable and fluctuations of data during the period can also be due to seasonal effect and market impulses. In order to learn more about the characteristics of these time series, central index of the average and three indexes of dispersion of standard deviation, maximum and minimum values were calculated for each one of the studied years.

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Table-1. Central and dispersion indexes of time series separately for the years studied.

2011	2010	2009	2008	2007	2006	2005	2004	2003	2002	Statistics
35917	28000	26375	30996	16542	14127	13355	12007	10645	9639	Average
1987	1966	1281	5339	2681	289	433	676	469	679	Standard deviation
39000	32000	28000	42500	23000	14550	13830	13180	11180	10600	Maximum value
33000	25000	24500	23750	14000	13700	12400	11100	9525	8500	Minimum value

Source: Findings from the research

Statistics showed that on average the final year of study, i.e., 2011 included the maximum retail price; while the first year of study, i.e., 2002 included the least retail price of Sadri - e - Momtaz rice. Studying the statistics value of standard deviation is indicates that in 2007 the highest fluctuations in retail price of rice have occurred during different months of this year. On the other hand, in 1385 the most stable price trends are included in different months of the year. Maximum recorded retail price of Sadri - e - Momtaz rice in 2007 was 42500 Rials, while minimum price was related to the year 2002, that is, 8500 Rials.

Table-2. Average price growth for different months during the years 2002-2011.

Average price Growth	Month	Average price growth	Month
2974	October	2592	April
3059	November	3024	May
2966	December	2915	June
2922	January	2936	July
3065	February	2835	August
3053	March	2934	September

Source: Findings from the research

Results showed that on average, growth in the retail price of Sadri - e - Momtaz rice had the highest and the least values in February and April, respectively.

Monthly time series modeling and forecasting about retail price of Sadri - e - Momtaz rice

Triple Exponential Smoothing approach (TES) is the most complete kind of non-parametric model of triple exponential smoothing which includes three smoothing parameters for data level, trend and seasonal effect. Like other exponential smoothing models, considering the minimization of MAPE error criterion in regard to within-sample forecasting, values of three adjustment parameters of alfa, beta and gama were determined, and they are 0.87, 0.01 and 0.26, respectively. Twelve-fold seasonal indexes of this time series are 0.99648, 1.03855, 1.01997, 1.03516, 1.01251, 0.9576, 0.95548, 0.99511, 1.00334, 0.99805, 0.99823 and 0.98951, respectively.

Index values of within sample prediction error MAD, MSE and MAPE for this model are 964, 4635303 and 3.79, respectively. The correlation value between the predicted and actual values of under consideration time series is also 98 percent. As noted, compared with other under consideration models, the simultaneous modeling of the trend and seasonal effect in this model has reduced the values of within sample prediction error. Out-sample prediction values of TES model for April, 2012 to March 2013 have been presented in the following table:

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Table-3. Out sample prediction values for April 2012 to March 2013 using the TES model.

Prediction value	month	Prediction value	Month
38862	October	39623	April
40706	November	41530	May
41111	December	40729	June
41177	January	41292	July
41480	February	40688	August
41380	March	38939	September

Source: Findings from the research

Seasonal auto-regressive integrated moving average (SARIMA)

In order to modeling time-series of monthly price of Sadri-e-Momtaz rice using parametric approach SARIMA, at first step using BM and Taylor test the presence of unit root in non-seasonal and seasonal frequencies was studied. And then, in order to select appropriate lags of dependent variable in BM test statistics LM was applied. In this context, acceptance of optimized pause considering the absence of autocorrelation and inconsistency conditional variance took place. The main variables used in fitting the BM model include trend, imaginary variables from D2 to D12 and twelve linear transformations of monthly retail prices of Sadri-e-Momtaz rice.

Table-4. Results from BM unit root test.

Critical amounts (at 5 % probability level)	Calculative value (model with intercept and trend)	Seasonal frequency	Test type
-3.44	-1.82	0	$t : \pi_1 = 0$ Test
-2.65	-3.37	π	$t : \pi_2 = 0$ Test
5.77	5.57	$\pi / 2$	$F : \pi_3 = \pi_4 = 0$ Test
5.77	12.77	$2\pi / 3$	$F : \pi_5 = \pi_6 = 0$ Test
5.77	7.77	$\pi / 3$	$F : \pi_7 = \pi_8 = 0$ Test
5.84	8.31	$5\pi / 6$	$F : \pi_9 = \pi_{10} = 0$ Test
5.84	11.71	$\pi / 6$	$F : \pi_{11} = \pi_{12} = 0$ Test

Source: Findings from the research

Since the absolute value of calculative statistics (1.82) t is less than the absolute value of critical statistics (3.44) in zero frequency, this is an indicative of the presence of non-seasonal or long term root in under consideration monthly time series. Also, in frequency of $\pi / 2$ since the value of calculative statistics F (5.57) is less than the value of critical statistics (5.77), this is an indicative of the presence of seasonal root in this frequency. For other seasonal roots in different frequencies, the greatness of calculative statistics compared to the critical value is an indicative of absence of seasonal root in that frequency. Statistics related to the diagnostic control tests of fitting BM model is presented in Table-5.

Table-5. Diagnostic control tests of fitting BM model.

ARCH (12)	ARCH (1)	LM (12)	LM (1)	Test type
1.57	0.02	0.87	0.86	Calculative statistics value
0.99	0.88	0.58	0.35	Probability level

Source: Findings from the research

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Calculative statistics value LM (1) is equal to 0.86 and greatness of probability level of this statistics than 0.05 or 5% is an indicative of acceptance of assuming zero and absence of autocorrelation. Also, in case of computational statistics LM (12) the value of probability level 0.58 is an indicative of acceptance of absence assumption on the basis of lack of autocorrelation in the fitted model. Also, in order to study the variance inconsistency test, the two ARCH (1) and ARCH (12) tests were used. The probability of both tests is greater than 5 percent and this shows the acceptance of assuming zero on the basis of absence of variance inconsistency in the fitted model. Due to the absence of variance autocorrelation and inconsistency, results related to t and F statistics are reliable. In order to check the simultaneous presence of all non-seasonal and seasonal roots, Taylor test of the type $F_{1, 2... 12}$ was used. Results from Taylor test have been shown in Table-6.

Table-6. Results from Taylor unit root test.

Critical value	Computational value	Seasonal frequency	Test type
5.82	97.45	$0, \pi, \dfrac{\pi}{2}, \dfrac{2\pi}{3}, \dfrac{\pi}{3}, \dfrac{5\pi}{6}, \dfrac{\pi}{6}$	$F : \pi_1 = ... = \pi_{12} = 0$ Test
4.5	105.3	$\pi, \dfrac{\pi}{2}, \dfrac{2\pi}{3}, \dfrac{\pi}{3}, \dfrac{5\pi}{6}, \dfrac{\pi}{6}$	$F : \pi_2 = ... = \pi_{12} = 0$ Test

Source: Findings from the research

Computational statistics $F_{1,2, ..., 12}$, being larger in absolute value than critical value is indicative of absence of all non-seasonal and seasonal roots. Also, the value of statistics $F_{2, ..., 12}$ is indicative of lack of all seasonal roots. According to the root 1 and $\pm i$ in under consideration data, the appropriate filter for changing the data into static form, is obtained from multiplying the two filters (1-L) and $(1+ L^2)$. In order to use the SARIMA model, filtered data is used and different steps of model fitness takes place on the basis of this data. After filtering the data for changing it into static nature, functions of ACF and PACF were formed and the degrees of the initial model of SARMA were selected. On this basis, the values of p=5, q=3, P=0 and Q=0 were considered for the model. Diagnostic statistics and goodness of fitness of the models (5, 3) (0, 0) SARMA were shown in Table-7.

Table-7. Summary of diagnostic statistics and goodness of fitness of SARMA models.

Probability level	Computational Value	Statistics
0.146	2.12	Q (beg.)
0.242	5.48	Q (12)
0.529	14.09	Q (24)
-	15.52	AIC
-	15.74	SC
-	0.5	R^2

Source: Findings from the research

The value of probability level of Q statistics with initial interruptions, 12 and 24 is greater than 5 percent or 0.05, and consequently the absence assumption, on the basis of absence of autocorrelation in (5, 3) (0, 0) SARMA model is accepted. In addition to the reported models in the above Table, other different degrees have also been considered but due to the significance of Q statistics and the presence of autocorrelation it was ignored. Results from fitting the mentioned model, is shown in Table-8.

In the following Table, AR (i) are indicative of autoregressive regression processes with interruptions of 1 to 5, respectively, and MA(j) are indicative of regression coefficients of average moving processes with interruptions of 1 to 3. α parameter is intercept of (5, 3) (0, 0) SARMA model.

Table-8. Results related to the fitting of (5, 3) (0, 0) SARMA model.

t statistics	Standard deviation	Regression coefficient	variable
-2.61	0.235	-0.613	AR(1)
-0.54	0.12	-0.06	AR(2)
-2.11	0.11	-0.24	AR(3)
-0.21	0.12	-0.02	AR(4)
0.98	0.01	0.09	AR(5)
-2.55	0.21	-0.54	MA(1)
-37.68	0.02	-0.96	MA(2)
-3.09	0.17	-0.54	MA(3)
1.4	648.5	906.4	α

Source: Findings from the research

Results showed that regression coefficients of AR (1), AR (3), MA (1), MA (2) and MA (3) at statistical level of 5 percent, is significant according to the t statistic values.

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After fitting and determining the model in order to evaluate the within sample prediction power, monthly observations related to the year 2010-2011 were created using the model, and the real values were compared.

Table-9. Evaluation of within sample prediction power of (5, 3) (0, 0) SARMA model.

Mar.	Feb.	Jan.	Dec.	Nov.	Oct.	Sep.	Aug.	July	June	May	Apr.	Val.
40466	35525	35992	38003	36410	35474	35165	36038	34553	31813	33444	31683	Predic.
39000	38500	36000	37500	36500	34500	35500	37000	36500	34000	33000	33000	Real
1466	2975	8	503	90	974	335	962	1947	2187	444	1317	Abs. differ (Rials)
3.76	7.73	0.02	1.34	0.25	2.82	0.94	2.6	5.33	6.43	1.34	3.99	Relat. difference percent

Source: Findings from the research

Given the above results the average value of absolute difference (MAD) in within sample prediction is 1101 Rials and the average value of relative difference is equal to 3 percent. Comparing the values of within sample prediction error Index of MAPE models showed that parametric SARMA model had the most power in modeling time series of monthly retail price of Sadri-e-Momtaz rice. Out-sample prediction values of SARMA for April 2012 to March 2013 have been presented in the following table.

Table-10. Out-sample prediction values for 2012-2013 using SARMA model.

Prediction value	Month	Prediction value	Month
40731	October	39723	April
40921	November	39298	May
41180	December	39654	June
41521	January	39900	July
41741	February	40295	August
41917	March	40555	September

Source: Findings from the research

SUMMARY AND RECOMMENDATIONS

In order to present a perspective of future income to producers of Sadri-e-Momtaz rice in Guilan province, modeling and predicting the future prices of this rice in different months of the year 2012-2013 was considered. Results from using parametric and non-parametric models are indicatives of it. Out sample prediction values for the year 2012-2013 by TES model shows that TES is the best kind of non-parametric model TES because it contains three smoothing parameters for modeling the data level, trend and seasonal effect. Index values of within sample prediction error MAD, MSE and MAPE for this model is 964, 4635303 and 3.79, respectively. The correlation value between the predicted values and real values of under consideration time series is also 98 percent. As it is evident from the present research, simultaneous modeling with the trend and seasonal effect in this model has decreased the values of within sample prediction error. TED model enjoys more accuracy because it is affected by the trend and seasonal effect.

In SARMA model after fitting and determining the model for the purpose of evaluating the within-sample prediction power, monthly observations related to the year 2011 was created using the model and was compared with real values. In this comparison the average amount of absolute difference (MAD) in within sample prediction was 1101 Rials and the average amount of Relative difference was 3 percent.

Finally, after comparison, the values of within sample prediction error index MAPE between the two non-parametric TES and Parametric SARMA models showed that SARMA parametric model has the most power in monthly retail price of Sadri-Momtaz rice, thus it is the most appropriate model for predicting monthly retail prices of Sadri-e-Momtaz rice. Many factors such as the large supply of product at harvest time, bank loan paying backs, environmental factors, religious and historic occasions, economic factors and supportive government policies affect the price of rice. The present research with the belief that expected prices impact on cultivation model provides an appropriate framework for productive planning for paddy farmers to use it to obtain appropriate and reasonable profit from product sales. Also, modeling the behavior of prices and predicting its value can have an

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important role in the performance planning for market regulation. Obviously, more relations of policy-making sectors with scientific centers in order to use such a modeling can be promising for future regional and national planning.

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